Update on Machine Learning Studies at FAST

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FAST/IOTA Collaboration Meeting

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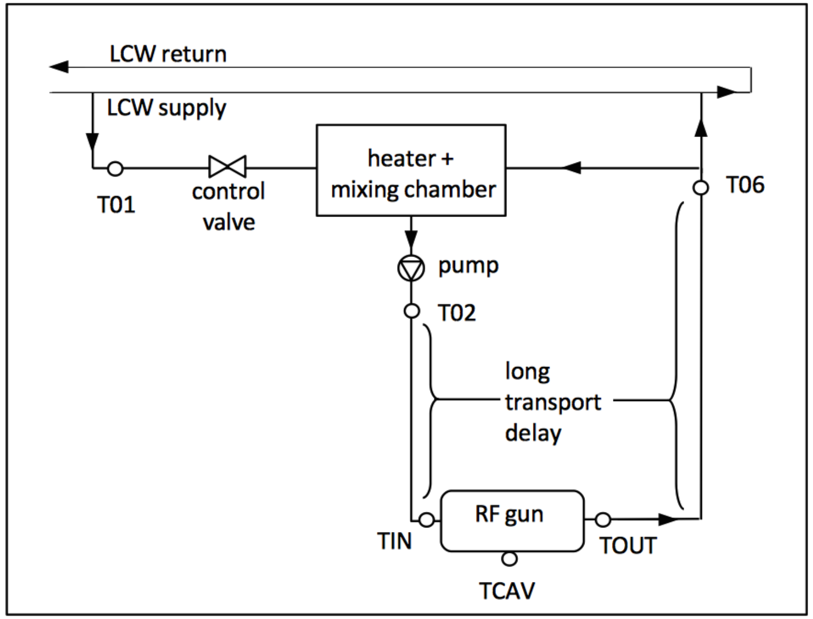
Temperature/Resonant Frequency Control for the RF Gun

Resonant frequency controlled via gun temperature

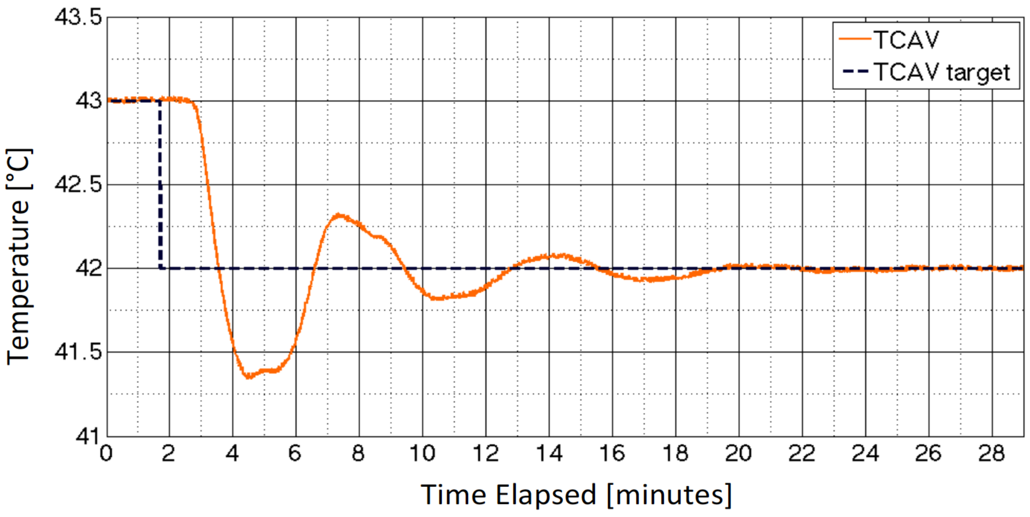
PID control is undesirable in this case:
- Long transport delays and thermal responses
- Recirculation leads to secondary impact of disturbances
- Two controllable variables: heater power + valve aperture

Applied model predictive control (MPC) with a neural network model trained on measured data: ~ 5x faster settling time + no large overshoot

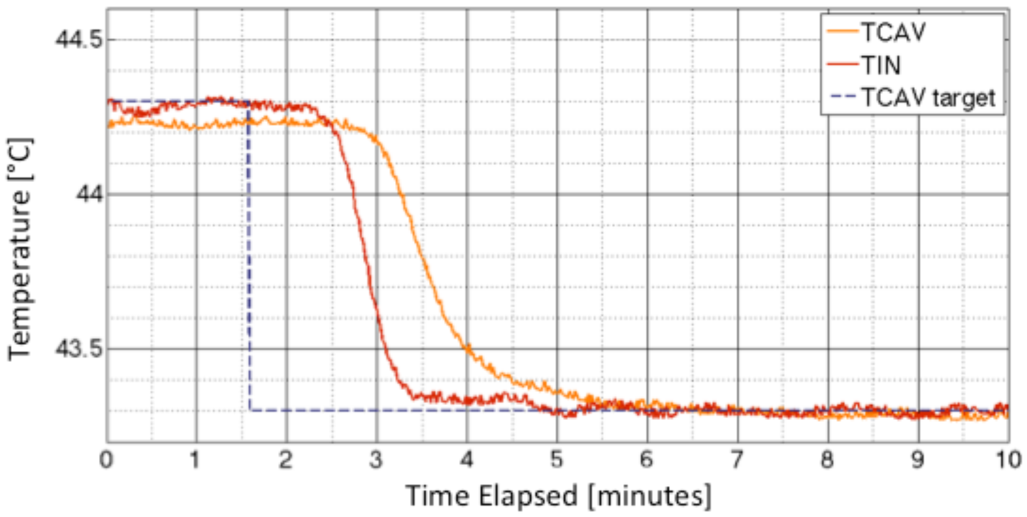
Gun Water System Layout



Existing Feedforward/PID Controller



Model Predictive Controller



Note that the oscillations are largely due to the transport delays and water recirculation, rather than PID gains

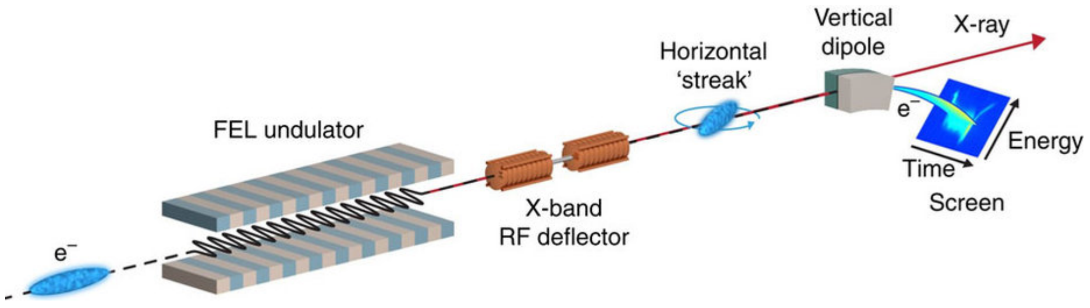
More info: A. L. Edelen et al., IEEE TNS, vol. 63, no. 2, 2016

That was an example of using a learned model and predictive control for a system with long-term time dependencies…

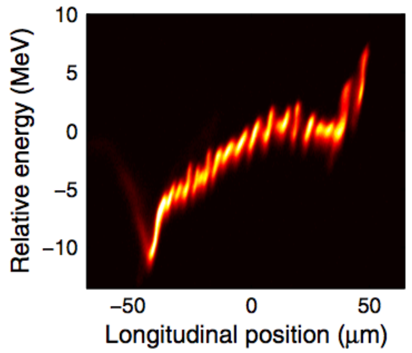
… what are some areas where a learned control policy might be useful?

- **Image diagnostics** → would be nice to use directly, and some yield relatively complicated information

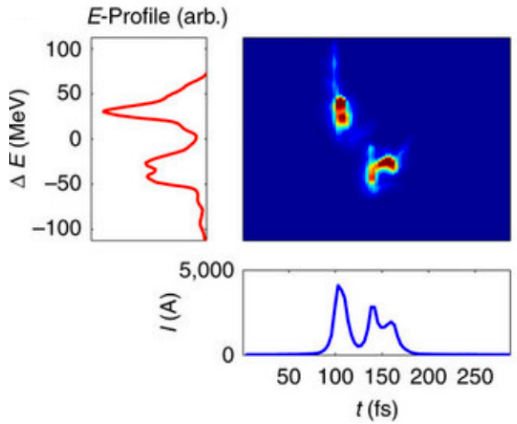
e.g. XTCAV at SLAC



C. Behrens, et al., Nat. Commun. **5**, 3762 (2014)



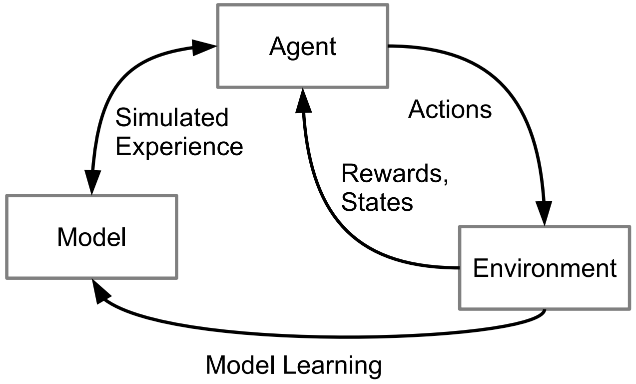
D. Ratner, et al., PRSTAB18, 030704 (2015)



A. Marinelli, et al., Nat. Commun. **6**, 6369 (2015)

- **Convolutional Neural Networks (CNNs)** → very good at image processing

- **Reinforcement Learning (RL)** → can learn control policies from data



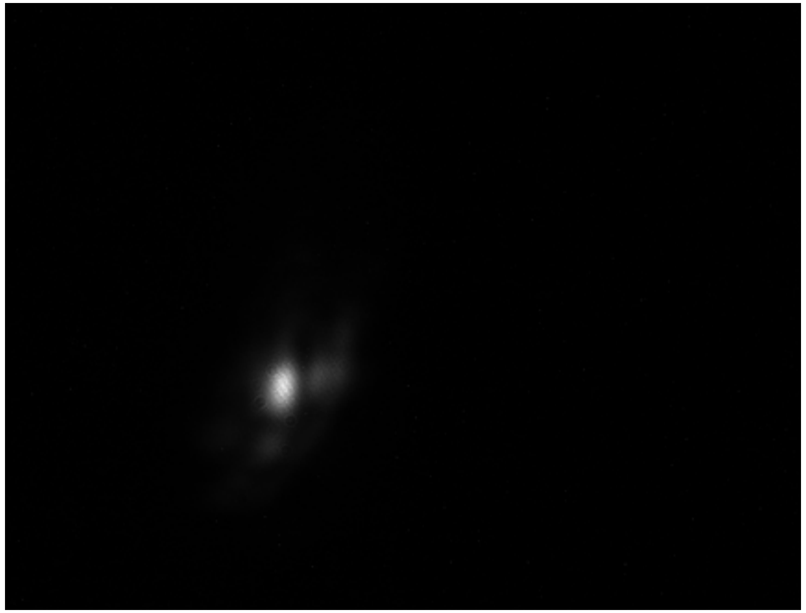
Why not try using image based diagnostics directly in learned control policies?

What's a relatively simple test case to start with?

Initial Study: Choose Gun Parameters Based on Laser Spot

Motivation:

- Gun phase and solenoid strength tuned daily
- Asymmetries in initial laser distribution result in emittance asymmetries downstream
- Would be nice to obtain optimal gun phase and solenoid strength for a given initial laser distribution automatically (and perhaps prioritize x or y emittance to minimize)



Example virtual cathode image (10 Aug. 2016)

Other perks:

- PARMELA simulation based on survey data already in existence (J. Edelen)
- Try out creating a fast NN modeling tool from slower-executing simulations

Initial Study: Choose Gun Parameters based on Laser Spo

Motivation:

- Gun phase and sole
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- PAR ... ta already in existence (J. Edelen)
- Try c ... NN modeling tool from slower-executing simulations

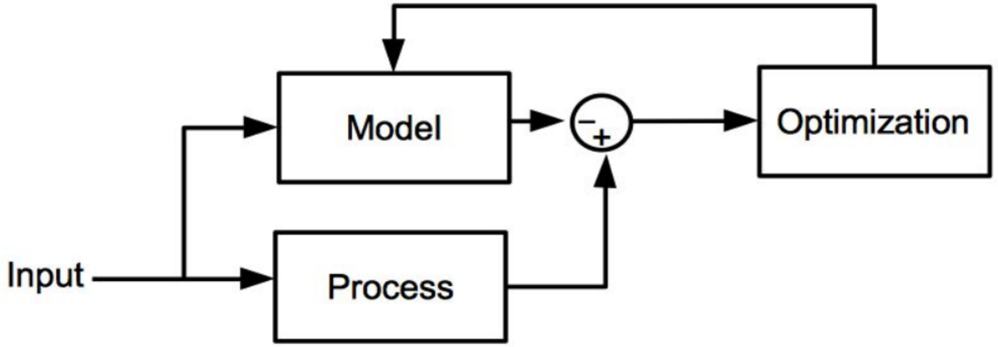
Why not just use online optimization?

Why not just fit a Gaussian to the laser spot to get the information instead of using images directly?

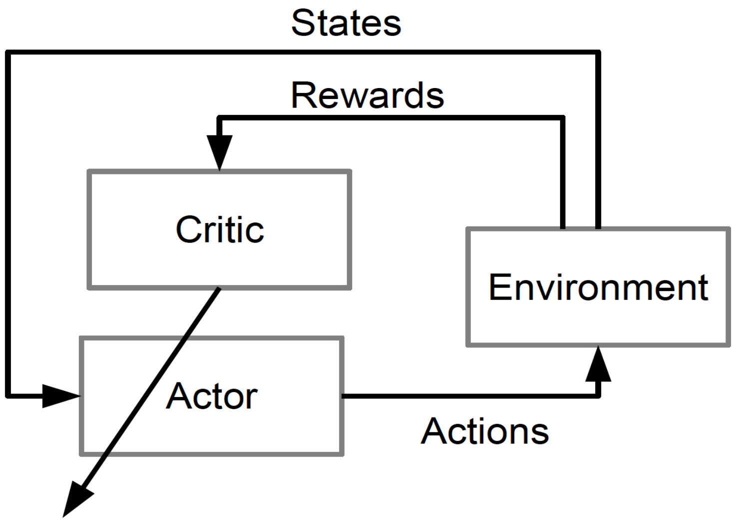
The point of this study: explore this approach on a simple system (it's a stepping stone)

Initial Study: Steps

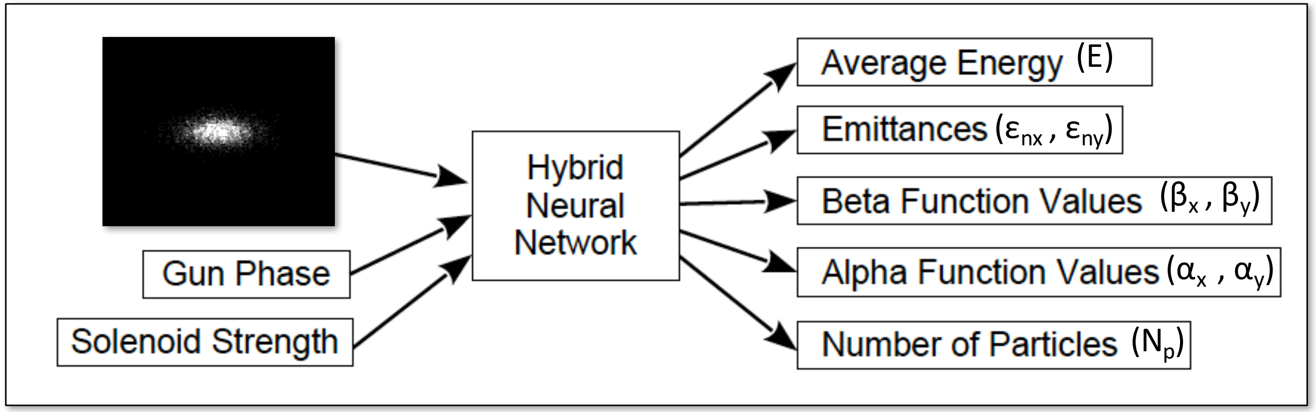
- Gather simulation data from PARMELA scans
- Create a NN model
  - Be certain that the necessary information can be extracted from the image, gun phase, and solenoid strength
- Train a RL controller using that model
- Extension beyond simulation (tentative):
  - Incorporate measured data into model and update controller
  - Carefully test on machine



Model Learning



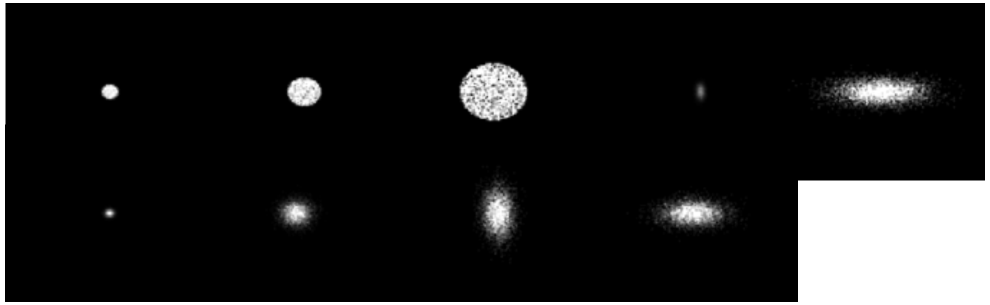
Policy Learning



model inputs and outputs

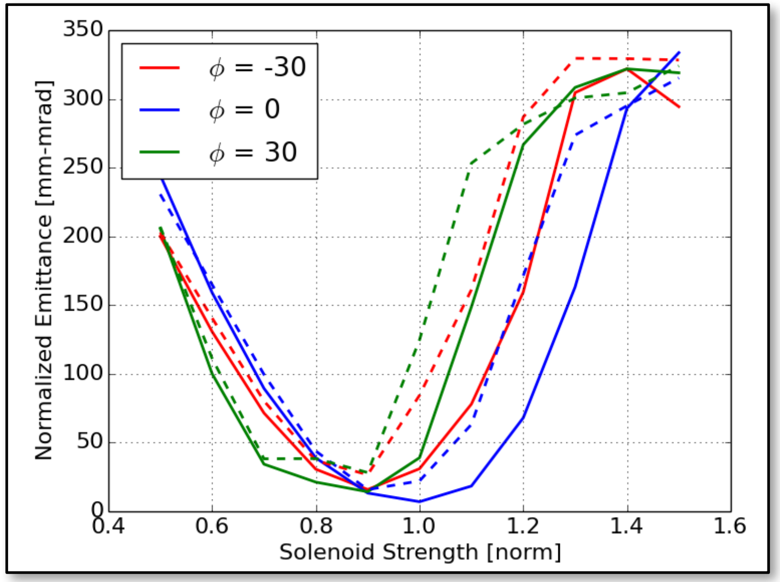
CNN Model: Simulation Data

- PARMELA simulations from the gun up to the exit of CC2
  - 2-D space charge routine
  - Scanned gun phase, solenoid strength, initial beam distribution
- Two sets of data:
  - Fine scans (steps of 5° phase, 5% sol. str.) for sims just past the gun
  - Coarse scans (steps of 10° phase, 10% sol. str.) for sims up through CC2
- Simulated "virtual cathode images"
  - Going from VCI → initial beam distribution ok from prior work
  - Initial beam distribution → simulated VCI probably ok
  - Obviously very "well-behaved" examples



Parameter Ranges used for Model Training

Parameter	Gun Data		CC2 Data	
	Max Value	Min Value	Max Value	Min Value
N_p	5001	1015	5001	1004
ε_{nx} [m-rad]	2.50E-04	1.60E-06	4.00E-04	9.10E-07
ε_{ny} [m-rad]	2.40E-04	1.60E-06	4.00E-04	8.50E-07
α_x [rad]	14.1	-775.1	0.8	-149.8
α_y [rad]	14.5	-797	0.7	-154.5
β_x [m/rad]	950.4	7.90E-02	820.2	0.7
β_y [m/rad]	896.8	8.40E-02	845.7	0.81
E [MeV]	4.6	3.2	47.2	42.8



Simulation predictions after CC2. Dashed lines are x-emittance, solid lines are y-emittance.

Caveat: doesn't take into account coupling…later changed NN setup to predict sigma matrix, and also used a 3D space charge routine.

For normalized sol strength, 1 is the setting that produces a peak axial field of 1.8 kG

CNN Model: Performance

Parameter	Train. MAE	Train. STD	Val. MAE	Val. STD
N_p	69.5	79.8	70.7	75.7
ε_{nx}	2.30E-06	3.50E-06	2.40E-06	3.20E-06
ε_{ny}	2.30E-06	3.40E-06	2.40E-06	3.20E-06
α_x	9	14.9	10.9	16
α_y	8.8	15.3	10.8	16.1
β_x	12.1	17.6	14.8	18.9
β_y	11.7	16.7	14.3	17.9
E	4.90E-03	4.90E-03	5.50E-03	6.00E-03

Performance for the predictions after the gun

Parameter	Train. MAE	Train. STD	Val. MAE	Val. STD
N_p	103.7	141.2	123.3	176.8
ε_{nx}	1.00E-05	1.20E-05	1.20E-05	1.60E-05
ε_{ny}	1.00E-05	1.30E-05	1.20E-05	1.50E-05
α_x	3.4	6.6	3.1	5.9
α_y	3.4	6.6	3.1	5.9
β_x	16.3	33.5	14.7	27.8
β_y	16.4	33.6	14.8	27.5
E	4.00E-02	3.90E-02	4.60E-02	6.20E-02

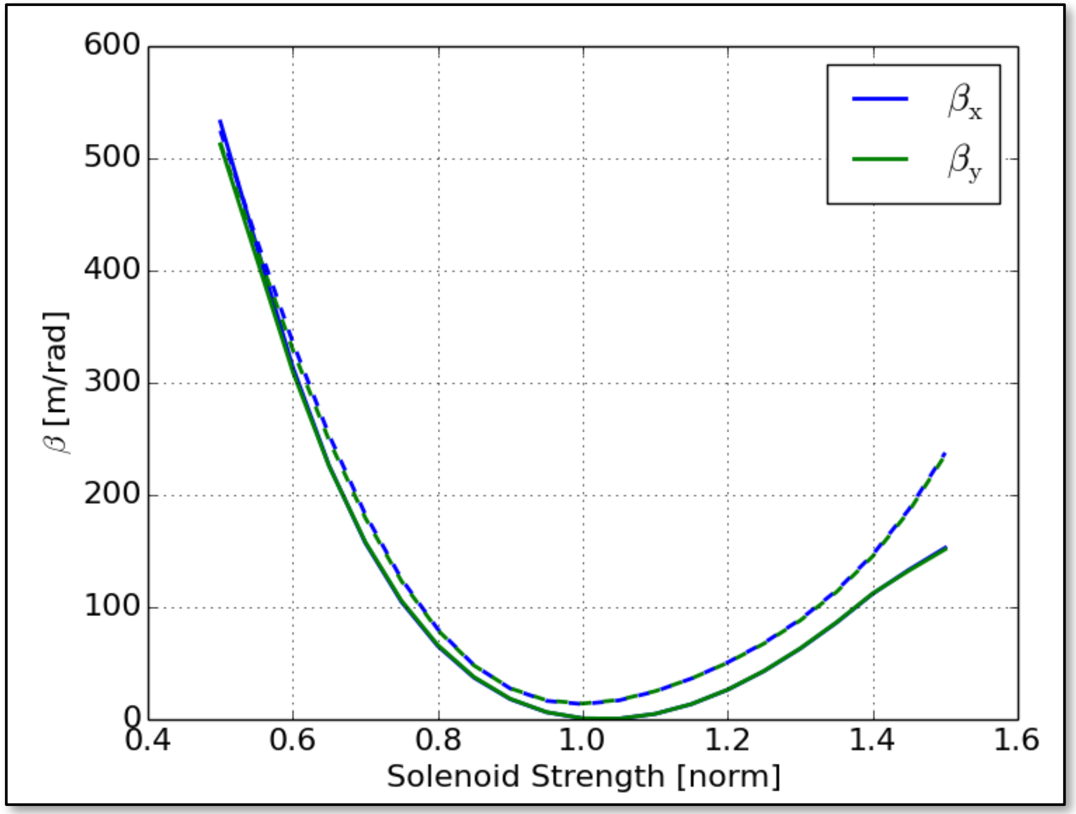
Performance for the predictions after CC2

For the gun data, all MAEs are between 0.4% and 1.8% of the parameter ranges.
For the CC2 data, all MAEs are between 0.9% and 3.1% of the parameter ranges.

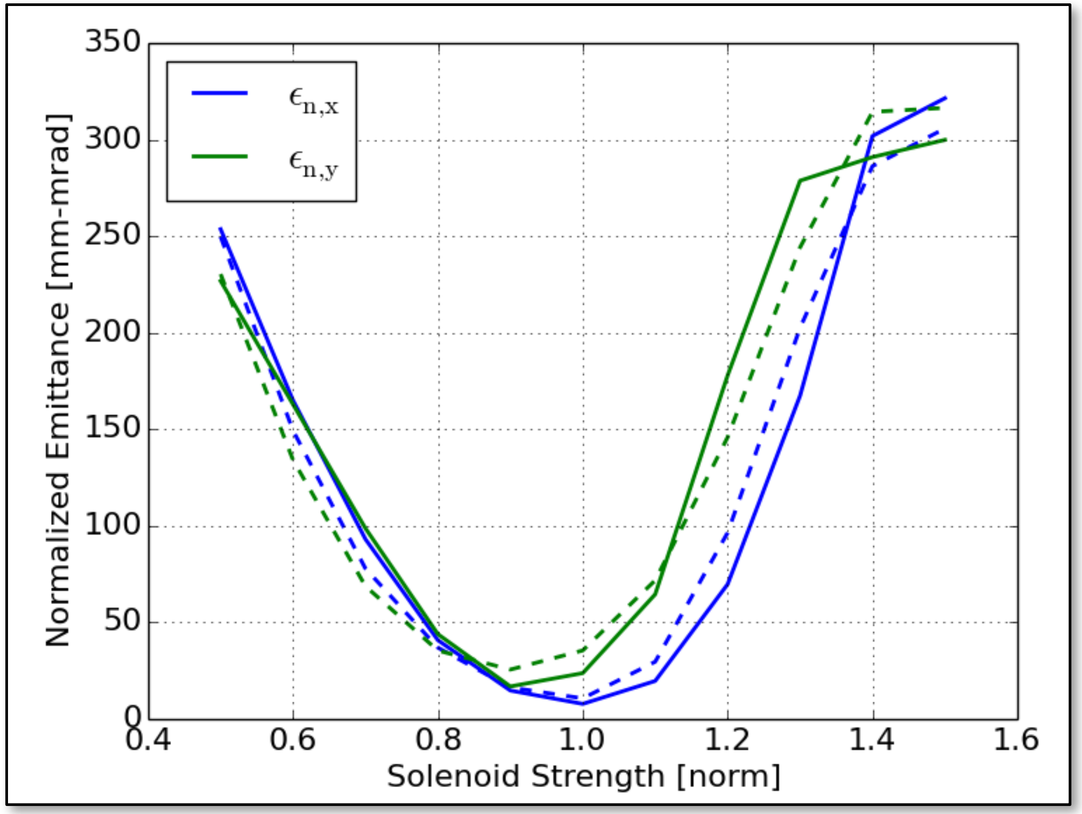
→ *Not bad for such a small training set*

CNN Model: Two Representative Plots

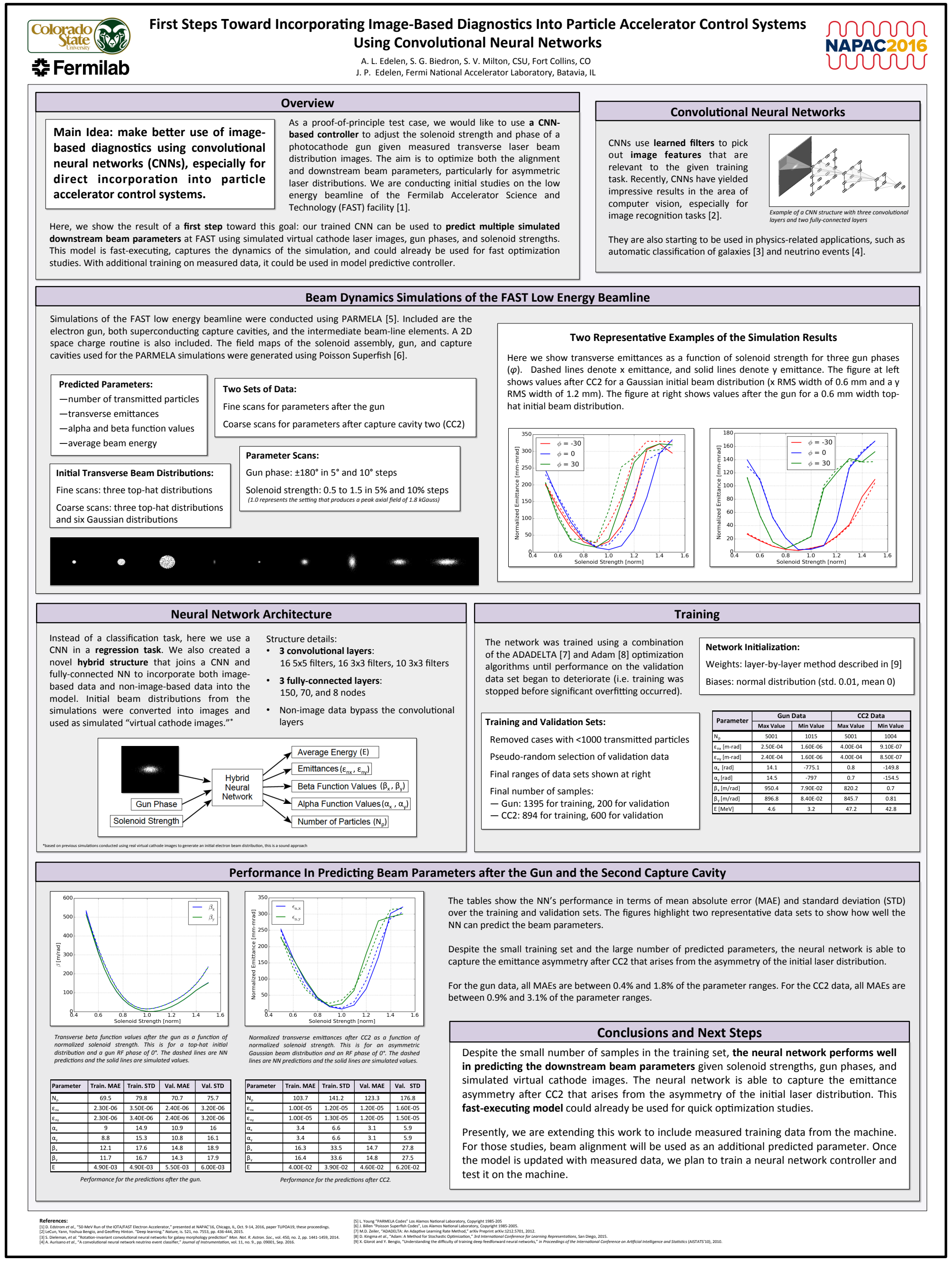
Dashed lines are NN predictions and solid lines are simulation results



Top-hat initial beam, 0° RF phase, after gun



Asymmetric Gaussian initial beam, 0° RF phase, after CC2



This work was presented at NAPAC '16

- TUPOA51, https://arxiv.org/abs/1612.05662
- One of the student poster contest winners

Present Status and Next Steps

- **Improving the quality of the setup:**
  - Predicting the full sigma matrix
  - More realistic initial distributions
  - Using 3D space charge routine
  - Using locally-connected layers
  - Switching to ASTRA

    (greater execution speed → more training data)

- **Expanding scope to phase space manipulations:**
  - Specify a target sigma matrix
  - Include quads after CC2, capture cavity phases, etc.
  - Collaborating with NIU:
    - RTFB transform is a possible application
    - Alex Halavanau running simulation scans with NIU's newer model → more training data

- **Next steps (in tandem):**
  - Finish simulation study with present setup
  - Extend to phase space manipulation simulation study
  - Solidify plans for incorporating measured data and testing controller
    - Need to align available inputs/controllable variables (e.g. sigma matrix vs. info from emittance monitors, rotation of quads, etc.)
    - Also depends on run schedule, status of new emittance monitors, solid time with consistent setup, etc.

Also, if you have some other possible application and have or can easily obtain training data: don't hesitate to get in touch!